Affordances for Machine Learning — Jenny L. Davis

Notes and Summary

Source:
Davis, J. L. (2021). *Affordances for Machine Learning*. The Australian National University.

Overview

Jenny L. Davis argues that machine learning (ML) systems should be understood as designed artifacts, much like tools or interfaces, rather than as purely technical systems or abstract social forces.

Key Argument:

- **Every part of an ML system—from data selection to model architecture, optimization parameters, and interfaces—embodies human design decisions that reflect cultural values, institutional priorities, and power relations**
- **ML systems could have been built differently, which means they carry the imprint of their makers' assumptions and therefore influence social structures and inequality**

Key Concepts

Affordances

Affordances describe how the features of a technology shape what people can do with it, including both direct actions and broader social effects.

- **They enable and constrain possible actions for people within specific social and institutional contexts**
- **Example: A "Like" button enables quick expression but constrains nuanced communication**

Affordance Theory in Design Studies

- **Central to fields such as UX, HCI, software design, law, robotics, education, and architecture**

- Serves as a conceptual middle ground between:
    - Technological determinism (technology fully determines social outcomes), and
    - Social constructivism (humans freely assign meaning)
- Emphasizes co-constitution: people and technologies shape each other dynamically

The Gap Between Principles and Practice

- The field of ML suffers from a persistent principles-to-practice gap—ethical codes and commitments often dissipate in application
- Affordance theory offers a way to bridge this gap by examining how technical design decisions translate into social consequences

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Why Design Matters for ML

Machine learning is deeply embedded in institutional systems—healthcare, finance, education, policing, and labor management.

Its affordances have direct consequences for how people live, work, and are evaluated:

- ML influences major decisions (e.g., credit approvals, hiring, policing, surveillance)
- It also mediates everyday life (e.g., recommendations, notifications, automation)

Because ML is designed within social systems, it is not neutral; it both reflects and shapes existing power structures.

Core Premises ("Ground Truths")

1. Technologies Are Social and Political

- Every technical system is a social construction, reflecting cultural and institutional values
- Design choices encode assumptions about who counts, what matters, and how the world should be structured
- Technologies actively distribute power by determining who benefits and who is excluded
- Example: Predictive policing encodes political assumptions about crime and resource allocation

2. Machine Learning Reproduces and Amplifies Inequality

- ML systems learn from historical data, which often contains structural bias
- As a result, they replicate and magnify existing inequalities (e.g., racism, sexism, classism)

Examples:

- **Facial recognition systems misidentifying women and people of color**
- **Credit-scoring models denying loans to marginalized groups**

3. Social Design Implies Malleability

- **If technologies are socially constructed, they can be redesigned differently**
- **Recognizing this opens space for ethical intervention, accountability, and equitable redesign**

Definition of Affordance (in this Paper)

> **"Affordances describe how the features of a technology shape what people can do with it—both in direct use and through wider social effects."**

Weaknesses in Traditional Affordance Theory

Binary Framing

- **Technologies are often described as either affording or not affording certain actions**
- **This ignores the degrees of influence (push, pull, enable, constrain) that technologies exert**

Universal Subject Assumption

- **Affordances are often discussed as if they apply uniformly to all users**
- **In reality, affordances vary across identity, culture, ability, and context**
- **This insight is particularly developed within disability studies, which demonstrates how design choices privilege some bodies and exclude others**

Toward a Refined Framework: Mechanisms and Conditions (M&C)

To address these shortcomings, Davis proposes the Mechanisms and Conditions Framework, which reconceptualizes affordances as dynamic, relational, and context-dependent.

Mechanisms (How Technologies Afford)

Affordances operate through mechanisms that exist on a continuum, not as binary options. Each mechanism represents a different degree of pressure or permission:

Mechanism	Description
Request	Gently initiates or invites an action
Demand	Strongly pressures for an action
Encourage	Supports user's intended action
Discourage	Resists or de-emphasizes an action
Refuse	Prevents the action entirely
Allow	Neutral enabling; space for action without push or pull

Example – Notifications:
Notifications request attention and discourage ignoring through repeated alerts. They allow customization but rarely encourage disengagement.

Conditions (For Whom, Under What Circumstances)

Affordances depend on user context across three interrelated dimensions:

Dimension	Description
Perception	Awareness of the option's existence

Dexterity	**Ability or skill to use it effectively**
Cultural & Institutional Legitimacy	**Whether the action is socially or institutionally supported**

Example – Silencing Notifications:
To silence alerts, a user must:

- **Know the feature exists (perception)**
- **Know how to access it (dexterity)**
- **Be in a setting where it is permitted (legitimacy)**

If any of these are missing, the affordance becomes restricted despite being technically available.

Application to Machine Learning

1. Accountability

- **The M&C framework provides a vocabulary to analyze ML's social and ethical impact**
- **Describing ML mechanisms as requests, demands, refusals, etc., makes hidden design choices legible and allows for accountability**

2. Analytical Tool

Researchers and auditors can use the framework to examine:

- **Which types of users are assumed or privileged**
- **How systems enable or block opportunities**
- **How sociotechnical structures reinforce existing hierarchies**

Example:
A hiring algorithm may encourage résumés with corporate language while refusing nontraditional backgrounds, reinforcing dominant norms.

3. Design Tool

The framework also guides ethical design, shifting the question from *what can this system do?* to *what should it afford socially?*

Potential ML affordances for equitable design:

- **Demand equity (require fairness across groups)**
- **Refuse discrimination (reject biased patterns)**
- **Request inclusivity (invite participation from marginalized groups)**
- **Allow plurality (enable multiple perspectives)**
- **Encourage representation of historically silenced voices**

4. Infrastructural Implications

Affordances exist across the entire ML pipeline:

- **Data Sources: Whose data is included or excluded**
- **Interfaces: How results are displayed and acted upon**
- **Cleaning Protocols: Which forms of "noise" or bias are removed or preserved**
- **Benchmarks: What defines "success" or "accuracy"**
- **Human Agency: Who can interpret, override, or challenge the model**
- **Institutional Context: What rules or norms guide system use**

Case Examples

Hiring Algorithms

Mechanism	Example Behavior
Request	Prompt applicants to upload résumés in specific formats
Demand	Reject files with incompatible fonts or formats
Encourage	Reward keyword-heavy résumés matching corporate culture
Discourage	Downrank applicants with employment gaps

Refuse	**Exclude non-accredited institutions**
Allow	**Permit cover letters but assign little algorithmic weight**

Conditions:

- **Perception: Awareness of relevant keywords**
- **Dexterity: Skill in optimizing résumés**
- **Legitimacy: Institutional acceptance of alternative credentials**

Predictive Policing Systems

- **Request: Suggest increased patrols in certain neighborhoods**
- **Demand: Require officers to input arrest data**
- **Encourage: Highlight hotspot zones, reinforcing prior biases**
- **Discourage: Rarely direct focus toward affluent areas**
- **Refuse: Cannot produce a "no-risk" result—always predicts some threat**
- **Allow: Officers can ignore suggestions but often face institutional pressure**

Conditions:

- **Perception: Community awareness of categorization**
- **Dexterity: Officers' ability to interpret outputs**
- **Legitimacy: Institutional support for overriding the system**

Content Recommendation Systems (YouTube / TikTok)

- **Request: Autoplay suggests the next video**
- **Demand: Require sign-in for personalization**
- **Encourage: Promote popular, high-engagement content**
- **Discourage: Reduce visibility of dissenting or niche voices**
- **Refuse: Flag or delete specific videos**
- **Allow: Enable subscriptions, though they are less prioritized than algorithmic feeds**

Conditions:

- **Perception: Awareness of curation**
- **Dexterity: Ability to modify settings**
- **Legitimacy: Support (or lack thereof) for marginalized creators**

Design Implications: Amazon Warehouse Example

Status Quo

- Data-driven management systems track workers constantly
- Mechanisms: Demand speed, discourage rest, refuse autonomy
- Results: Reduced worker agency and increased surveillance

Redesign Proposals

Proposal	Mechanism Shift	Affordance Effect
Depersonalize Tracking	From demand surveillance → refuse personal data collection	Encourages efficiency while allowing privacy
Loosen Time Rates	From demand speed → allow variation	Encourages safety and discourages burnout
Reconfigure Scheduling	From demand flexibility → allow predictability	Encourages work–life balance and accountability

Outcome:
These redesigns prioritize human dignity and safety over efficiency metrics, demonstrating that technical infrastructures can be reconfigured to redistribute power more equitably.

Broader Takeaways

Whose Perspective Counts

- Affordance analysis depends on inclusivity
- Marginalized communities often perceive harms invisible to privileged designers
- Design and audit processes should therefore center diverse perspectives

The Role of the M&C Framework

- **Provides a shared vocabulary for analyzing, redesigning, and critiquing ML systems**
- **Makes explicit how technical choices produce social consequences**
- **Translates ethical reflection into practical design and accountability tools**

Beyond Technical Solutions

- **The framework does not "solve AI," but clarifies the links between design, power, and inequality**
- **By making these connections visible, it renders them actionable for change**

Summary

The Mechanisms and Conditions (M&C) framework reframes ML systems as sociotechnical artifacts that afford actions, shape behavior, and distribute power.

It emphasizes that ML affordances are:

- **Dynamic — shifting across time and context**
- **Relational — dependent on users' capacities and environments**
- **Malleable — open to redesign for equitable outcomes**

Understanding ML through affordances transforms design from a neutral technical task into a moral and political practice.